J Arid Land (2024) 16(5): 603–614
https://doi.org/10.1007/s40333-024-0013-3

Science Press Springer-Verlag

Landscape ecological risk assessment and its driving factors in the Weihe River basin, China

CHANG Sen, WEI Yaqi, DAI Zhenzhong, XU Wen, WANG Xing, DUAN Jiajia, ZOU Liang, ZHAO Guorong, REN Xiaoying, FENG Yongzhong*

College of Agronomy, Northwest A&F University, Yangling 712100, China

Abstract: Weihe River basin is of great significance to analyze the changes of land use pattern and landscape ecological risk and to improve the ecological basis of regional development. Based on land use data of the Weihe River basin in 2000, 2010, and 2020, with the support of Aeronautical Reconnaissance Coverage Geographic Information System (ArcGIS), GeoDa, and other technologies, this study analyzed the spatial-temporal characteristics and driving factors of land use pattern and landscape ecological risk. Results showed that land use structure of the Weihe River basin has changed significantly, with the decrease of cropland and the increase of forest land and construction land. In the past 20 a, cropland has decreased by 7347.70 km², and cropland was mainly converted into forest land, grassland, and construction land. The fragmentation and dispersion of ecological landscape pattern in the Weihe River basin were improved, and land use pattern became more concentrated. Meanwhile, landscape ecological risk of the Weihe River basin has been improved. Severe landscape ecological risk area decreased by 19,177.87 km², high landscape ecological risk area decreased by 3904.35 km², and moderate and low landscape ecological risk areas continued to increase. It is worth noting that landscape ecological risks in the upper reaches of the Weihe River basin are still relatively serious, especially in the contiguous areas of high ecological risk, such as Tianshui, Pingliang, Dingxi areas and some areas of Ningxia Hui Autonomous Region. Landscape ecological risk showed obvious spatial dependence, and high ecological risk area was concentrated. Among the driving factors, population density, precipitation, normalized difference vegetation index (NDVI), and their interactions are the most important factors affecting the landscape ecological risk of the Weihe River basin. The findings significantly contribute to our understanding of the ecological dynamics in the Weihe River basin, providing crucial insights for sustainable management in the region.

Keywords: land use; ecological risk; spatiotemporal distribution; geographic detector; driving factors

Citation: CHANG Sen, WEI Yaqi, DAI Zhenzhong, XU Wen, WANG Xing, DUAN Jiajia, ZOU Liang, ZHAO Guorong, REN Xiaoying, FENG Yongzhong. 2024. Landscape ecological risk assessment and its driving factors in the Weihe River basin, China. Journal of Arid Land, 16(5): 603–614. https://doi.org/10.1007/s40333-024-0013-3

1 Introduction

Global changes have triggered numerous ecological and environmental issues, which have been increasingly concerned by the international community (Mishra et al., 2022). Research indicates that human-induced alterations in land use represent one of the most significant pathways for affecting terrestrial ecosystems (Zhang et al., 2022). Thus, research on land-use-driven ecological risk has emerged as a hot topic in ecology. The earliest framework for ecological risk assessment

*Corresponding author: FENG Yongzhong (E-mail: fengyz@nwsuaf.edu.cn)
Received 2023-12-08; revised 2024-03-28; accepted 2024-04-17

can be traced back to the 1990s, introduced by the U.S. Environmental Protection Agency, which elucidated the fundamental concepts of ecological risk (Tian et al., 2019). In its early stage, ecological risk assessment primarily relied on identified ecological risk source to evaluate their potential impact on ecosystems (Peng et al., 2015), and was typically employed for assessing environmental contamination processes associated with individual risk source (Kim et al., 2014). However, with the continuous development of ecological risk assessment theories and models, the research focus has shifted from individual risk source to the overall ecosystem impact and spatial characteristics of ecological risk, and the assessment scale has also been expanded to the regional landscape pattern level (Tang and Ma, 2018). Landscape patterns encompass fundamental information concerning surface landscape structure and type, providing a comprehensive reflection of both natural and anthropogenic influences on land disturbance and regional ecological functionality (Liu et al., 2020), which is essential to guide sustainable development of the region (Xing et al., 2020).

Landscape ecological risk is based on the land-use perspective and landscape patterns (Zhang et al., 2016; Wang et al., 2020; Xu et al., 2021). It can be employed to comprehensively analyze the potential impacts on different ecological environments, providing effective information for protective measures. Some studies employ various landscape pattern indices to construct ecological risk indices, thereby assessing ecological risk at different spatial scales, such as lake (Xie et al., 2013), urban area (Zhou et al., 2014), and habitat of animals (Chen et al., 2020). Furthermore, the exploration of driving factors behind landscape ecological risk is a current research hotspot. Recently, research often employs methods such as boosting regression tree (Mo et al., 2021), correlation analysis (Karimian et al., 2020), geographically weighted regression (Yu et al., 2019), and geographic detector analysis (Chen et al., 2022b) to investigate the factors influencing landscape ecological risk. Compared with other methods, geographic detector analysis can better detect driving factors and explain the interaction between them.

The Weihe River basin is one of the most important cultural and agricultural areas in China. Rapid economic growth, coupled with the persistent influences of natural attributes and human activities inevitably results in ecological stress and landscape ecological change within the Weihe River basin. There is an urgent need to enhance regional ecological comprehensive management of this basin. Thus, the main objectives of this study are: (1) to analyze the spatio-temporal characteristics of land use and landscape patterns in the Weihe River basin; (2) to establish an assessment model to reveal the spatio-temporal variations of landscape ecological risk from 2000 to 2020; and (3) to investigate the driving factors of landscape ecological risk by using geographic detector analysis.

2 Materials and methods

2.1 Study area

The Weihe River basin (33°50′–37°18′N, 104°00′–110°20′E), located in the central China, spans across two provinces (Shaanxi and Gansu) and one autonomous region (Ningxia Hui Autonomous Region), covering a total area of approximately 1.34×10^5 km^2. The basin falls within the continental monsoon climate zone and serves as a transitional area between semi-arid and semi-humid regions. Annual precipitation ranges from 500 to 700 mm. The topography of the Weihe River basin features a west-to-east elevation gradient, gradually transitioning from higher elevation in the west to gentler terrain in the east. The northern part is the Loess Plateau, while the southern region comprises the Qinling Mountains. The predominant landforms within the basin include loess hilly areas, loess plateaus, earth-rocky mountainous regions, loess terraces, and valley alluvial plains. As the primary tributary of the Yellow River, the Weihe River basin holds a dense population and has experienced steady economic growth. It occupies an important position in the strategic planning of ecological protection and high-quality development of the Yellow River basin.

2.2 Data sources

Land use data in 2000, 2010, and 2020 were sourced from the CLCD (China Land Cover Dataset) produced by Yang and Huang (2021). The administrative boundary data for the Weihe River basin were obtained from the National Cryosphere Desert Data Center (https://www.ncdc.ac.cn). We performed precise delineation of the land use data by cropping it based on the administrative boundaries of the study area, thereby yielding land use data for the Weihe River basin in 2000, 2010, and 2020. The predominant land use categories within the study area encompass cropland, forest land, shrub land, grassland, water body, and barren land. The 30 m normalized difference vegetation index (NDVI) dataset is obtained from the National Ecosystem Science Data Center (Yang et al., 2019). The 1 km×1 km annual average temperature and annual total precipitation data were provided by the UK National Centre for Atmospheric Science (NCAS) (https://crudata.uea.ac.uk). The 30 m×30 m elevation data were obtained from the Geospatial Data Cloud (http://www. gscloud.cn), and we calculated the slope based on the elevation data. The 1 km×1 km population density data were sourced from the WorldPop (https://www.worldpop.org). The long-term annual artificial nighttime light data for China were acquired from the National Tibetan Plateau Data Center (Zhang et al., 2021).

2.3 Methods

2.3.1 Land use and land cover (LULC) change

Utilizing the dynamic degree formula with a specific LULC allows for computing alterations in LULC over a defined temporal interval within the study area (Moussa Kourouma et al., 2022). Chen et al. (2022a) proposed that shifts in land use types over extended periods can be elucidated through the creation of transition matrices. The article employs a LULC transition matrix to depict the rules governing transitions among various LULC categories, as illustrated in the subsequent equations.

$$P_{T+1} = X_{ij} \times P_T, \tag{1}$$

$$X_{ij} = \begin{bmatrix} X_{11} & \dots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{n1} & \dots & X_{nn} \end{bmatrix}, \ 0 \le X_{ij} < \text{land} \sum_{j=1}^{n} X_{ij} = 1, \ \left(i, j = 1, 2, \ \cdots, n\right), \tag{2}$$

where X_{ij} is the probability that type i is transferred to type j in LULC, and i, j are the first and the second LUCC types, respectively; P_T and P_{T+1} are the status of land use at time T and time T+1, respectively; and n is the number of LULC in the study area.

2.3.2 Landscape pattern index

Landscape pattern indices efficiently summarize regional landscape pattern data and effectively represent the spatial arrangement and dynamic alterations within the regional ecological environment. In alignment with the research objectives and the unique characteristics of the Weihe River basin, this study opted for six specific landscape pattern indices at landscape level. These indices encompass the number of patches (NP), patch density (PD), edge density (ED), landscape shape index (LSI), average patch area (AREA), and shannon diversity index (H'). Calculations were performed using Fragstats v.4.2 software (https://fragstats.org/).

2.3.3 Landscape ecological risk assessment

A regional ecological risk assessment model was developed by integrating the landscape disturbance index and vulnerability index. The landscape disturbance index (Q_i) quantifies the extent of loss experienced by various landscape types following disturbances, with higher Q_i values indicating increased ecological risk.

$$Q_i = aZ_i + bY_i + cW_i, \tag{3}$$

$$Z_i = \frac{f_i}{g_i}, \tag{4}$$

$$Y_i = \frac{G}{2g_i}\sqrt{\frac{f_i}{G}}, \tag{5}$$

$$W_i = \frac{1}{4}\left(\frac{f_i}{F} + \frac{e_i}{E}\right) + \frac{g_i}{2G}, \tag{6}$$

where Z_i is the landscape fragmentation index; Y_i is the landscape isolation index; and W_i is the landscape dominance index; a, b, and c are coefficients that represent the weights assigned to the respective indices concerning landscape disturbance, and the values are 0.5, 0.3, and 0.2, respectively (Chang et al., 2023); f_i, g_i, G, e_i, E, and F are the number of patches, total area (m^2), total landscape area (m^2), the number of sampling units with the occurrence of patch type i, the total number of sampling units, and the total number of patches, respectively.

Landscape ecological risk assessment model translates the spatial arrangement of land use types into ecological risk at a spatial scale, effectively quantifying the level of ecological loss within the assessed units. Considering the average size of landscape patches within the study area and data processing capability (Huang and He, 2016; Xiang et al., 2021), this study partitioned the Weihe River basin into a grid with the dimension of 6 km×6 km, resulting in a total of 3807 units. The landscape ecological risk values for each grid unit were computed, and a quantile classification method was employed to categorize the study area into four ecological risk levels, including the low, moderate, high, and severe landscape ecological risk.

$$ERI_k = \sum_{i=1}^{n} \frac{A_{ki}}{A_i}\left(Q_i V_i\right), \tag{7}$$

where ERI_k is the ecological risk index of assessment unit k; n is the number of landscape types; A_{ki} is the area of the i^{th} landscape type within assessment unit k (km^2); A_i is the area of assessment unit k (km^2); and V_i is the landscape fragility index.

As indicated in previous research (Chang et al., 2023), V_i values for various landscape types are as follows: cropland (0.133), grassland (0.092), water body (0.294), forest land (0.037), shrub land (0.052), construction land (0.02), and barren land (0.373). It should be noted that higher V_i values signify a decreased resilience of landscape types when facing external perturbation.

2.3.4 Spatial distribution correlation analysis

Spatial auto-correlation analysis could reflect the spatial clustering of a variable or geographic phenomenon in a certain area or its neighboring areas. The commonly used correlation index is Moran's I index (Anselin, 1995). In this study, local indicators of spatial association cluster maps of landscape ecological risk were created using GeoDa software, and the result of cluster was divided into four types of regional spatial differentiation: high-high clustering, high-low clustering, low-high clustering, and low-low clustering.

2.3.5 Geographic detector

Geographic detector is a spatial statistical method used to reveal the spatial differentiation of geographic elements and their main influencing factors (Wang and Xu, 2017). The factors affecting landscape ecological risk are complex and could be broadly categorized into natural factors and socio-economic factors. Geographic detector is consisted of four components: risk detector, factor detector, ecological detector, and interaction detector. The geographical detector values of influencing factors are measured using the q-value, expressed by Equation 8.

$$q = 1 - \frac{\mathrm{SSW}}{\mathrm{SST}} = 1 - \frac{1}{N\sigma^2}\sum_{h=1}^{L} N_h \sigma_h^2, \tag{8}$$

where q is the degree of influencing factors on the spatial distribution of landscape ecological risk, ranging from 0 to 1. A higher q value indicates a stronger explanatory power of influencing factors on the spatial distribution of landscape ecological risk; SSW and SST are the sum of within-layer variances and the total variance of entire area, respectively; N is the total number of units in the area; σ^2 is the variance of variable Y value in the entire area; L is the stratification of

variable Y or influencing factor X; N_h is the number of units in stratum h; and σ_h^2 is the variance of variable Y in stratum h.

3 Results

3.1 Land use characteristics and landscape ecological patterns

In general, land use structure in the Weihe River basin is predominantly characterized by cropland and grassland, as shown in Figure 1, of which cropland accounts for the largest proportion. In 2020, cropland and grassland accounted for approximately 38.05% and 33.71%, respectively, followed by forest land and construction land. In the past 20 a, land use structure of the Weihe River basin has changed significantly, with the decrease of cropland and the increase of forest land and construction land. From 2000 to 2020, the area of cropland decreased by 7347.70 km^2, while the forest land, construction land, and water body increased by 4969.84, 2188.66, and 79.07 km^2, respectively. Compared with the period 2000–2010, land use change during the period 2010–2020 indicated a slower rate of cropland decrease, an increased proportion of forest land, and relatively stable grassland. At present, the Weihe River basin is experiencing rapid urbanization, leading to a significant expansion in construction land, which has increased from 1834.54 km^2 in 2000 to 4023.20 km^2 in 2020.

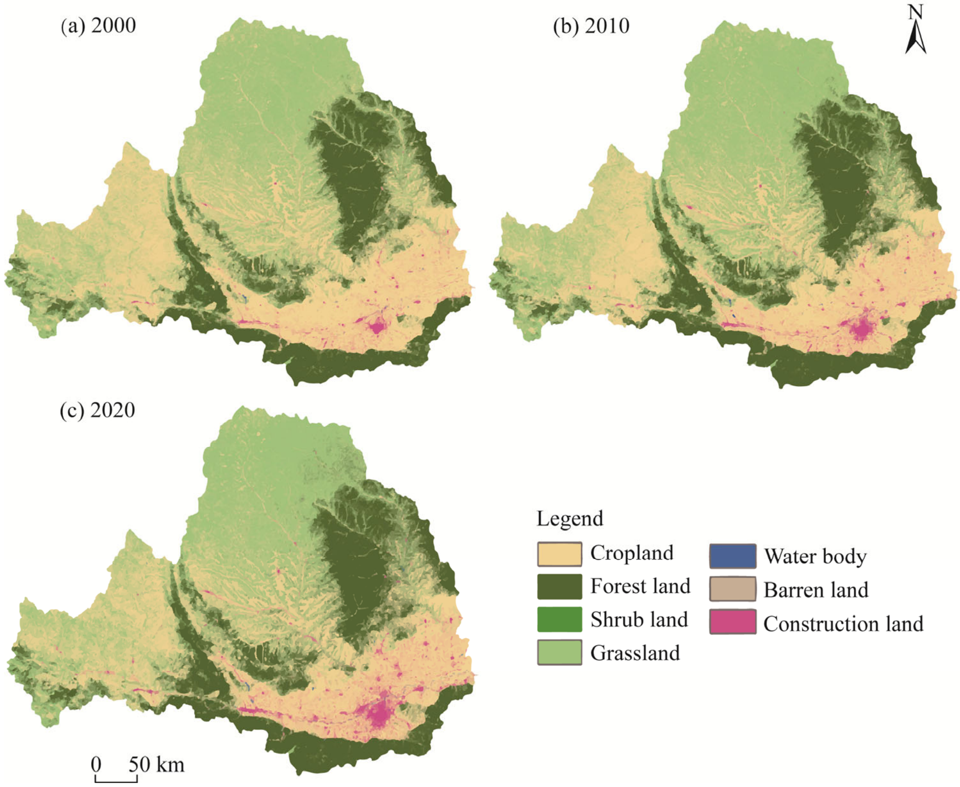

Fig. 1 Spatio-temporal variation of land use types in the Weihe River basin from 2000 to 2020. (a), 2000; (b), 2010; (c), 2020.

Land use transition matrix provided information about land type transformation in the Weihe River basin (Table 1). From 2000 to 2020, the area of cropland transformed into forest land, grassland, and construction land were 1598.89, 9365.88, and 2135.01 km^2, respectively. Cropland and grassland were the primary sources of expansion for construction land. On the other hand, grassland had a net conversion into forest land with an area of 3560.36 km^2, which was the major

source for forest land expansion, followed by cropland. From 2000 to 2020, the area of cropland in the Weihe River basin decreased, but there were still 5468.17 km^2 of grassland and 328.71 km^2 of forest land converted into cropland. And 6.95 km^2 of construction land has been reclaimed. In summary, there was a net transfer of 5167.88 km^2 from cropland to forest land and grassland, closely related to Chinese policies promoting the conversion of cropland into forest land and afforestation. In addition, it can be seen from the land use transfer matrix that cropland is the largest source of construction land expansion, which inevitably increases the pressure on cropland, making cropland protection in the area an important concern.

Table 1 Land use transfer matrix in the Weihe River basin from 2000 to 2020

Land use type	Cropland	Forest land	Shrub land	Grassland	Water body	Barren land	Construction land
				(km^2)			
Cropland	45,430.50	1598.89	2.73	9365.88	73.28	8.18	2135.01
Forest land	328.71	28,323.06	20.55	72.67	0.08	0.01	1.54
Shrub land	8.98	161.02	33.64	105.26	0.00	0.00	0.01
Grassland	5468.17	3633.04	45.68	35,875.27	14.63	5.05	74.84
Water body	23.19	0.44	0.00	1.20	70.91	0.04	11.63
Barren land	0.27	0.00	0.00	1.46	0.15	0.38	0.21
Construction land	6.95	0.02	0.00	0.16	27.43	0.03	1799.96

From 2000 to 2020, landscape ecological pattern in the Weihe River basin showed a declining trend in NP, PD, ED and LSI, while AREA and *H*' showed an increasing trend (Table 2). In general, it indicated that the fragmentation and dispersal of landscape ecological pattern in the Weihe River basin have improved, resulting in a more concentrated land use pattern.

Table 2 Changes in landscape ecological pattern indices in the Weihe River basin

Year	NP	PD (numbers/km^2)	ED	LSI	AREA (km^2)	*H*'
2000	1,619,590	12.02	72.13	664.24	8.32	1.14
2010	1,401,248	10.40	64.25	591.95	9.62	1.17
2020	1,503,770	11.16	69.48	639.93	8.96	1.20
Change rate (%)	–7.15	–7.15	–3.67	–3.66	7.70	5.71

Note: NP, number of patches; PD, patch density; ED, edge density; LSI, landscape shape index; AREA, average patch area; *H*', Shannon diversity index.

3.2 Spatio-temporal variations in landscape ecological risk

Landscape ecological risk in the Weihe River basin exhibited significant spatio-temporal variations, as shown in Figures 2 and 3. On the whole, landscape ecological risk of the Weihe River basin has been improved. Specifically, the area of severe landscape ecological risk decreased from 60,605.38 km^2 in 2000 to 41,427.51 km^2 in 2020, and the area of high landscape ecological risk decreased by 3904.35 km^2 over the 20-a period. In contrast, the area of low landscape ecological risk continued to increase, rising from 21,088.68 km^2 in 2000 to 30,397.07 km^2 in 2010, and further to 34,218.68 km^2 in 2020 (Fig. 2). The proportions of low, moderate, high, and severe landscape ecological risk area had also changed significantly, from 16.31%, 15.32%, 21.49%, and 46.88% in 2000 to 26.47%, 23.02%, 18.47%, and 32.05% in 2020, respectively. From a spatial distribution perspective, high landscape ecological risk areas in the Weihe River basin are mainly located in the upper reaches of the Weihe River and its major tributaries, while low landscape ecological risk areas are primarily situated in the northern Qinling Mountains (Fig. 3). With the application of ecological management projects, landscape ecological risk in the northern Weihe River basin have been significantly improved, and high landscape ecological risk areas have

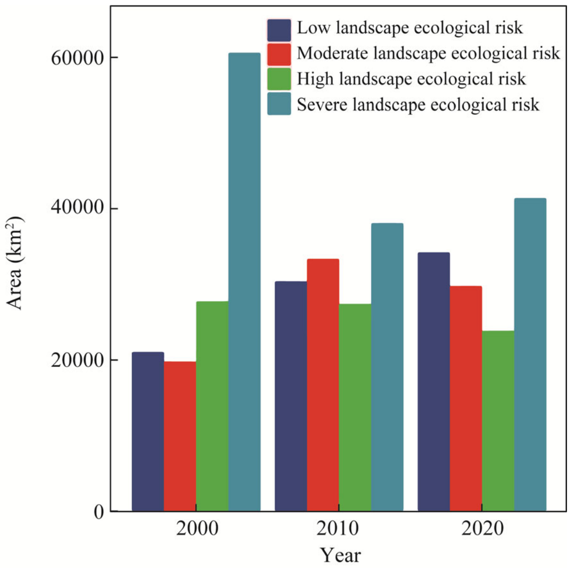

Fig. 2 Area of landscape ecological risk at different levels in the Weihe River basin from 2000 to 2020

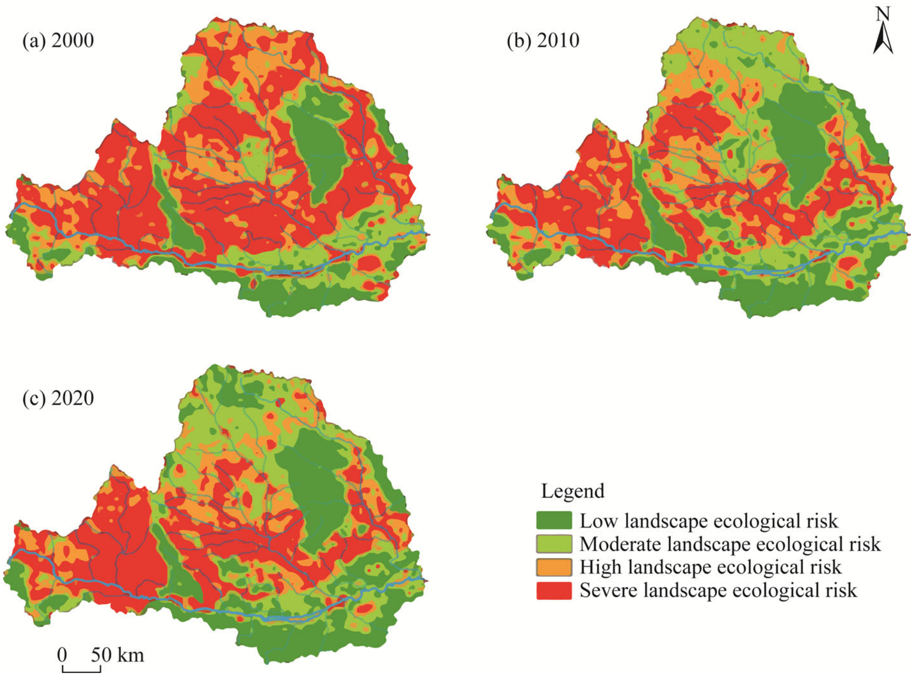

Fig. 3 Spatio-temporal variation of landscape ecological risk classification in the Weihe River basin from 2000 to 2020. (a), 2000; (b), 2010; (c), 2020.

gradually shown a discrete distribution trend. It is worth noting that the landscape ecological risk in the upper reaches of the Weihe River was still relatively serious, and there were consecutive serious ecological risk areas, such as Tianshui, Pingliang, Dingxi areas and some areas of Ningxia Hui Autonomous Region.

3.3 Spatial auto-correlation analysis of landscape ecological risk

GeoDa software was used to conduct spatial auto-correlation analysis of landscape ecological risk in the Weihe River basin in 2000, 2010, and 2020, and the results showed that the Moran's I indices were 0.131, 0.120, and 0.144, respectively (P<0.050), which suggested that landscape

ecological risk in the Weihe River basin had an obvious spatial positive correlation during the study period. In addition to non-significant areas, high-high and low-low clustering areas of landscape ecological risk were relatively common. High-high clustering was predominantly distributed Dingxi, Tianshui, Pingliang, Guyuan areas, as well as parts of Xianyang and Tongchuan areas. The low-low clustering was primarily observed in mountainous areas, such as the Qinling Mountains, Liupan Mountains, and Huanglong Mountains. High-low clustering and low-high clustering areas were relatively rare (Fig. 4). High-value of landscape ecological risk was mainly concentrated in areas with poorer ecological conditions, which were subject to significant human disturbances, resulting in elevated landscape ecological risk. From 2000 to 2020, there was a trend of decreasing high landscape ecological risk areas, but its spatial distribution was more concentrated. This result indicated that ecological environment quality of the Weihe River basin has been improved. Nonetheless, some areas within the basin still faced severe ecological risk.

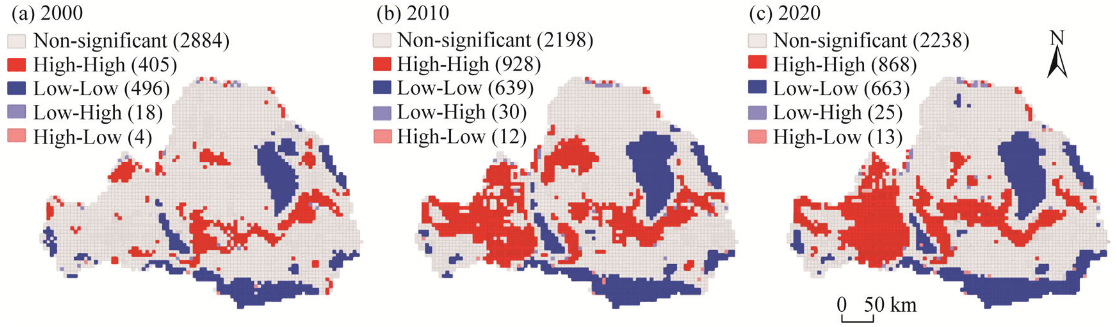

Fig. 4 Spatial auto-association cluster of landscape ecological risk in the Weihe River basin from 2000 to 2020. Values in brackets represent the number of grids. (a), 2000; (b), 2010; (c), 2020.

3.4 Driving factors for landscape ecological risk

The study selected a total of 7 driving factors, including five natural factors (NDVI (*X*3), annual precipitation (*X*4), annual temperature (*X*6), digital elevation model (DEM, *X*1), and slope (*X*2)) and two socio-economic factors (population density (*X*5) and night light (*X*7)). After calculation by using geographic detector, the contributions of these factors to spatial distribution of landscape ecological risk are shown in Figure 5. The contribution rates of various driving factors varied in different years. In 2000, the ranking of contribution rates for each factor was the following sequence: *X*4>*X*5>*X*6>*X*1>*X*3>*X*7>*X*2; in 2010, it was the following sequence: *X*5>*X*4>*X*3>*X*6>

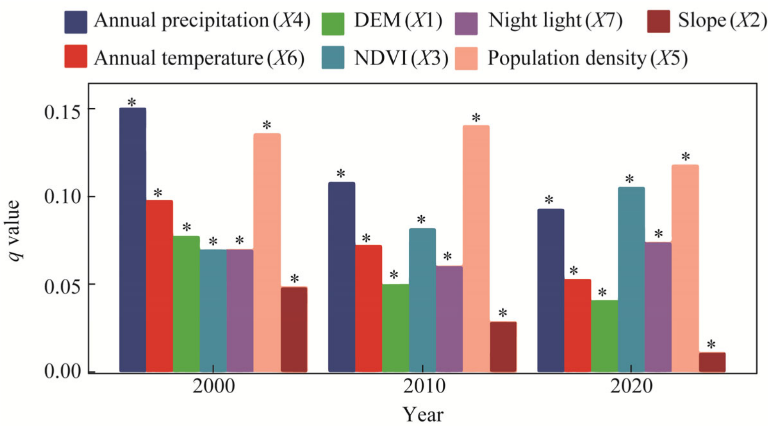

Fig. 5 The q values of driving factors in geographic detector from 2000 to 2020. * indicates that P value is less than 0.001 and q value has significant influence. The q value indicates the influence degree of driving factors on spatial distribution of landscape ecological risk. NDVI, normalized difference vegetation index; DEM, digital elevation model.

$X7>X1>X2$; and in 2020, it was $X5>X3>X4>X7>X6>X1>X2$. In general, population density, precipitation, and NDVI were the top three factors affecting landscape ecological risk. Precipitation significantly influenced the distribution pattern of ecological landscapes, especially in arid area. Population density is a representation of the intensity of human activities. NDVI exhibited a clear opposite spatial distribution trend compared with landscape ecological risk. Thus, these results could be well explained.

In general, the spatial differentiation of landscape ecological risk is not influenced by a single factor but by the interaction of multiple factors. It can be inferred from Table 3 that the interactions of driving factors generally have a more significant impact on landscape ecological risk in the Weihe River basin compared with single driving factor. In 2000, 2010, and 2020, the interaction effects (q values) of population density and NDVI were consistently the highest, indicating that they had the greatest impact on landscape ecological risk. Other significant interaction effects among driving factors included precipitation and population density, temperature and precipitation, and NDVI and temperature.

Table 3 Interaction of different driving factors in geographic detector

Year	Driving factor	DEM (*X*1)	Slope (*X*2)	NDVI (*X*3)	Annual precipitation (*X*4)	Population density (*X*5)	Annual temperature (*X*6)
2000	Slope (*X*2)	0.11					
	NDVI (*X*3)	0.18	0.14				
	Annual precipitation (*X*4)	0.20	0.19	0.19			
	Population density (*X*5)	0.18	0.16	0.22	0.22		
	Annual temperature (*X*6)	0.11	0.13	0.20	0.22	0.18	
	Night light (*X*7)	0.12	0.10	0.13	0.20	0.15	0.13
2010	Slope (*X*2)	0.07					
	NDVI (*X*3)	0.18	0.14				
	Annual precipitation (*X*4)	0.17	0.14	0.18			
	Population density (*X*5)	0.18	0.16	0.24	0.22		
	Annual temperature (X6)	0.10	0.10	0.20	0.21	0.18	
	Night light (*X*7)	0.13	0.10	0.14	0.19	0.18	0.14
2020	Slope (*X*2)	0.06					
	NDVI (*X*3)	0.18	0.15				
	Annual precipitation (*X*4)	0.14	0.11	0.17			
	Population density (*X*5)	0.15	0.14	0.23	0.21		
	Annual temperature(*X*6)	0.08	0.07	0.20	0.16	0.16	
	Night light (*X*7)	0.14	0.11	0.16	0.20	0.18	0.16

Note: NDVI, normalized difference vegetation index; DEM, digital elevation model.

4 Discussion

In recent years, China has been actively promoting the ecological management and development of the Weihe River basin. As an important component of high-quality development strategy for the Yellow River basin, ecological condition of the Weihe River basin is of paramount importance. Over the past 20 a, the land use structure of the Weihe River basin has undergone significant transformations, characterized by a decline in cropland and a notable increase in forest land and construction land. These changes reflect broader ecological restoration efforts and urbanization processes. While our findings align with the trends observed by Chen et al. (2022c), a deeper analysis is warranted to explore the multiple drivers and implications of these shifts in land use. Long-term ecological restoration has facilitated the transformation of low-yield cropland into forest land and grassland (Wang et al., 2019). Although the cropland has decreased, it has improved land use efficiency, increased forest land and grassland, and is of significant importance

for soil and water conservation and ecological security. Grain for Green program is an important measure for the high-quality development of the Yellow River basin. However, the process of urbanization is an inevitable trend in socio-economic development. Rapid urban expansion has intensified the tension between people and land resources (Yao et al., 2017), driving changes in land use structure (Song and Pijanowski, 2014) and promoting landscape ecological change in the Weihe River basin.

The spatio-temporal variation of landscape ecological risk in the Weihe River basin showed a positive trend. Its characteristic was a reduction in high landscape ecological risk areas and an increase in low landscape ecological risk areas. The result indicated that ecological protection and land use adjustment had a positive impact on ecological quality in the study area (Li et al., 2019). However, targeted ecological restoration efforts should prioritize remaining high landscape ecological risk areas, especially in the upper reaches of the Weihe River basin. These areas still exhibit relatively serious landscape ecological risk, and targeted ecological restoration measures should be taken to maintain and enhance these positive changes. These efforts may include maintaining the health and sustainable development of forest land and grassland, strengthening ecological restoration projects, controlling erosion, and establishing a robust ecological compensation mechanism. The study identified several key driving factors that significantly affected landscape ecological risk in the Weihe River basin, especially population density, NDVI, and precipitation. The impact of anthropogenic disturbances caused by human activities on natural environment and ecosystems has increased (Liu et al., 2018). Areas with high population density are positively correlated with increased landscape ecological risk, highlighting the importance of considering human activities and urbanization in ecological risk management. NDVI is inversely correlated with landscape ecological risk, with higher NDVI values indicating a more stable ecosystem. Thus, strategies to promote vegetation growth and maintain high NDVI values should be considered as part of efforts to reduce landscape ecological risk (Wang et al., 2024). Meteorological factors have become significant natural driving forces affecting landscape ecological security, particularly in arid areas, where precipitation plays a crucial role in mitigating ecological risk (He et al., 2020). Future climate change and precipitation pattern changes may affect landscape ecological risk, and we should incorporate climate adaptation measures into regional planning to address potential ecological risk arising from precipitation pattern change. Previous studies have particularly emphasized the importance of interactions among various driving factors with spatial heterogeneity (Wang et al., 2023). It is consistent with our findings. Therefore, we recommend that ecological environments require an integrated approach to achieve more effective risk management.

The study utilized various methods, including geographic detectors, and combined multi-temporal land-use data to establish an assessment system for landscape ecological risk in the Weihe River basin. It revealed the driving forces behind the spatial evolution of landscape ecological risk offered new approaches and perspectives for comprehensive ecological environmental protection in the entire Weihe River region. However, there are still several issues that need to be further studied. The first is the continuous monitoring and analysis of long-term trends in landscape ecological risk, which is essential to assess the effectiveness of ecological conservation and restoration. Further research is needed to investigate the potential impacts of climate change on landscape ecological risk and to develop adaptive strategies. Additionally, exploring the role of other socioeconomic factors in shaping landscape ecological risk, such as land use policy and economic development, can enhance our understanding of this complex issue.

5 Conclusions

The study employed spatial analysis and statistical techniques to analyze land use patterns, spatio-temporal characteristics of landscape ecological risk, and their driving factors in the Weihe River basin over the past 20 a. The results showed significant changes in the land use structure, marked by a decline in cropland and a noticeable increase in forest land and construction land.

Fragmentation and dispersion of landscape pattern within the basin have improved, and land use pattern became more concentrated. The overall landscape ecological risk in the Weihe River basin has been improved. The areas of severe landscape ecological risk and high landscape ecological risk decreased, while the areas of low landscape ecological risk continued to increase. Landscape ecological risk exhibited significant spatial dependence, showing a clear clustering effect with high-risk areas forming clusters. Landscape ecological risk in the upper reaches of the Weihe River was relatively serious, with contiguous areas of high landscape ecological risk, such as in areas like Tianshui, Pingliang, Dingxi, and some areas in Ningxia Hui Autonomous Region. Population density, precipitation, and NDVI are identified as the primary driving factors influencing landscape ecological risk. We emphasized that the interactions between driving factors have a more significant impact on ecological risk than a single factor. Thus, a more targeted and comprehensive approach is needed to achieve more effective ecological risk management. The study not only contributes to understanding the dynamics of landscape ecological risk in the Weihe River basin, but also provides robust data support for regional ecological conservation policy and sustainable land use. Additionally, our findings offer valuable insights for landscape ecological risk management beyond the study area, serving as a methodological framework and providing targeted recommendations for ecosystem conservation effort.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was funded by the National Natural Science Foundation of China (31971859), the Doctoral Research Start-up Fund of Northwest A&F University, China (Z1090121109), and the Shaanxi Science and Technology Development Plan Project (2023-JC-QN-0197).

Author contributions

Conceptualization: CHANG Sen, WANG Xing; Methodology: CHANG Sen, WEI Yaqi; Formal analysis: CHANG Sen, DAI Zhenzhong; Writing-original draft preparation: CHANG Sen; Writing-review and editing: XU Wen, DUAN Jiajia, ZOU Liang, ZHAO Guorong, REN Xiaoying; Funding acquisition: FENG Yongzhong, WANG Xing. All authors approved the manuscript.

References

Anselin L. 1995. Local indicators of spatial association—LISA. Geographical Analysis, 27(2): 93–115.

Chang S, Dai Z, Wang X, et al. 2023. Landscape pattern identification and ecological risk assessment employing land use dynamics on the Loess Plateau. Agronomy-Basel, 13(9): 2247, doi: 10.3390/agronomy13092247.

Chen H, Zhao Y, Fu X, et al. 2022a. Impacts of regional land-use patterns on ecosystem services in the typical agro-pastoral ecotone of northern China. Ecosystem Health and Sustainability, 8(1): 2110521, doi: 10.1080/20964129.2022.2110521.

Chen H, Zhou D, Zhang J, et al. 2022b. Ecological risk assessment of Gansu section of Weihe River Basin based on landscape pattern. Agricultural Engineering, 12(11): 72–79. (in Chinese)

Chen J, Dong B, Li H, et al. 2020. Study on landscape ecological risk assessment of hooded crane breeding and overwintering habitat. Environmental Research, 187: 109649, doi: 10.1016/j.envres.2020.109649.

Chen Y, Li H, Karimian H, et al. 2022c. Spatio-temporal variation of ozone pollution risk and its influencing factors in China based on Geodetector and Geospatial models. Chemosphere, 302: 134843, doi: 10.1016/j.chemosphere.2022.134843.

He C, Pu J, Shen J. 2020. Spatial-temporal changes and driving mechanisms of landscape ecological security in lower reaches of Lancang River during 2005–2018. Bulletin of Soil and Water Conservation, 40(4): 219–227. (in Chinese)

Huang M Y, He X. 2016. Landscape ecological risk assessment and its mechanism in Chaohu Basin during the past almost 20 years. Journal of Lake Sciences, 28(4): 785–793.

Karimian H, Chen Y, Tao T, et al. 2020. Spatiotemporal analysis of air quality and its relationship with meteorological factors in the Yangtze River Delta. Journal of Elementology, 25(3): 1059–1075.

Kim S, Kwak J, Yoon J, et al. 2014. Selection of domestic test species suitable for Korean soil ecological risk assessment.

Journal of Korean Society of Environmental Engineers, 36(5): 359–366.
Li Q, Zhang Z, Wan L, et al. 2019. Landscape pattern optimization in Ningjiang River Basin based on landscape ecological risk assessment. Acta Geographica Sinica, 74(7): 1420–1437. (in Chinese)
Liu C, Zhang K, Liu J. 2018. A long-term site study for the ecological risk migration of landscapes and its driving forces in the Sanjiang Plain from 1976 to 2013. Acta Ecologica Sinica, 38(11): 3729–3740. (in Chinese)
Liu D, Chen H, Zhang H, et al. 2020. Spatiotemporal evolution of landscape ecological risk based on geomorphological regionalization during 1980–2017: A case study of Shaanxi Province, China. Sustainability, 12(3): 941, doi: 10.3390/su12030941.
Mishra A, Humpenoder F, Churkina G, et al. 2022. Land use change and carbon emissions of a transformation to timber cities. Nature Communications, 13(1): 4889, doi: 10.1038/s41467-022-32244-w.
Mo Y, Li Q, Karimian H, et al. 2021. Daily spatiotemporal prediction of surface ozone at the national level in China: An improvement of CAMS ozone product. Atmospheric Pollution Research, 12(1): 391–402.
Moussa Kourouma J, Phiri D, Hudak A T, et al. 2022. Land use/cover spatiotemporal dynamics, and implications on environmental and bioclimatic factors in Chingola District, Zambia. Geomatics, Natural Hazards and Risk, 13(1): 1898–1942.
Peng J, Zong M, Hu Y, et al. 2015. Assessing landscape ecological risk in a Mining City: A case study in Liaoyuan City, China. Sustainability, 7(7): 8312–8334.
Song W, Pijanowski B. 2014. The effects of China's cultivated land balance program on potential land productivity at a national scale. Applied Geography, 46: 158–170.
Tang L, Ma W. 2018. Assessment and management of urbanization-induced ecological risks. International Journal of Sustainable Development and World Ecology, 25(5): 383–386.
Tian P, Li J, Gong H, et al. 2019. Research on land use changes and ecological risk assessment in Yongjiang River basin in Zhejiang Province, China. Sustainability, 11(10): 2817, doi: 10.3390/su11102817.
Wang B, Ding M, Li S, et al. 2020. Assessment of landscape ecological risk for a cross-border basin: A case study of the Koshi River Basin, central Himalayas. Ecological Indicators, 117: 106621, doi: 10.1016/j.ecolind.2020.106621.
Wang J, Xu C. 2017. Geographical detector: Principle and prospect. Acta Geographica Sinica, 72(1): 27–116. (in Chinese)
Wang S, Liu F, Chen W, et al. 2024. Landscape ecological risk evaluation and driving factors in the lake basin of central Yunnan Plateau. Chinese Journal of Eco-Agriculture, 32(3): 391–404. (in Chinese)
Wang X, Adamowski J F, Wang G, et al. 2019. Farmers' willingness to accept compensation to maintain the benefits of urban forests. Forests, 10(8): 691, doi: 10.3390/f10080691.
Xiang J, Li X, Xiao R, et al. 2021. Effects of land use transition on ecological vulnerability in poverty-stricken mountainous areas of China: A complex network approach. Journal of Environmental Management, 297: 113206, doi: 10.1016/j.jenvman.2021.113206.
Xie H, Wang P, Huang H. 2013. Ecological risk assessment of land use change in the Poyang Lake eco-economic zone, China. International Journal of Environmental Research and Public Health, 10(1): 328–346.
Xing L, Hu M, Wang Y. 2020. Integrating ecosystem services value and uncertainty into regional ecological risk assessment: A case study of Hubei Province, Central China. Science of the Total Environment, 740: 140126, doi: 10.1016/j.scitotenv.2020.140126.
Xu W, Wang J, Zhang M, et al. 2021. Construction of landscape ecological network based on landscape ecological risk assessment in a large-scale opencast coal mine area. Journal of Cleaner Production, 286: 125523, doi: 10.1016/j.jclepro.2020.125523.
Yang J, Dong J, Xiao X, et al. 2019. Divergent shifts in peak photosynthesis timing of temperate and alpine grasslands in China. Remote Sensing of Environment, 233: 111395, doi: 10.1016/j.rse.2019.111395.
Yang J, Huang X. 2021. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. Earth System Science Data, 13(8): 3907–3925.
Yao Y, Li X, Liu X, et al. 2017. Sensing spatial distribution of urban land use by integrating points-of-interest and Google Word2Vec model. International Journal of Geographical Information Science, 31(4): 825–848.
Yu T, Bao A, Xu W, et al. 2019. Exploring variability in landscape ecological risk and quantifying its driving factors in the Amu Darya Delta. International Journal of Environmental Research and Public Health, 17(1): 79, doi: 10.3390/ijerph17010079.
Zhang C, Bin D, Liping L, et al. 2016. Study on ecological risk assessment for land-use of wetland based on different scale. Journal of the Indian Society of Remote Sensing, 44: 821–828.
Zhang C, Zhao L, Zhang H, et al. 2022. Spatial-temporal characteristics of carbon emissions from land use change in Yellow River Delta region, China. Ecological Indicators, 136: 108623, doi: 10.1016/j.ecolind.2022.108623.
Zhang L, Ren Z, Chen B, et al. 2021. A prolonged artificial nighttime-light dataset of China (1984–2020). National Tibetan Plateau/Third Pole Environment Data Center. [2023-05-09]. https://doi.org/10.11888/Socioeco.tpdc.271202.
Zhou D, Shi P, Wu X, et al. 2014. Effects of urbanization expansion on landscape pattern and region ecological risk in Chinese coastal city: A case study of Yantai City. The Scientific World Journal, 2014: 821781, doi: 10.1155/2014/821781.